Advanced Indoor Localisation Based on the Viterbi Algorithm and Semantic Data

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***Abstract*—In this work a real-time indoor localisation system based on the Viterbi algorithm is developed. This Viterbi principle is used in combination with semantic data to improve the accuracy: i.e., the environment of the object that is being tracked and an adjustable maximum speed. The developed algorithm was verified by simulations and with experiments in a building-wide testbed for sensor and WiFi experiments. Compared to a reference algorithm without Viterbi or semantic data, the results indicated a significant improvement: the mean accuracy and standard deviation improved by respectively 26.4% and 63.9%.**

***Index Terms*—Localisation, Viterbi Algorithm, Semantic Data, Wireless Networks, Indoor Environment**

I. Introduction

Indoor localisation systems have applications in many domains, think of the healthcare sector, agricultural sector, industrial sector, cultural sector, etc. Examples of these applications are: tracking of elderly, monitoring of animals, equipment tracking and museum guidance. To locate an object, most localisation systems use a mobile node and a fixed infrastructure, which consists of static nodes. These static nodes are connected and form the wireless network. The mobile and fixed nodes exchange signals and the characteristics of these signals are used to estimate the position of the mobile node. Due to the complexity of many indoor environments, localisation systems are often not sufficiently accurate. Current state-of-the-art localisation systems try to improve the accuracy by using new technologies like Ultra Wideband (UWB) [1]. The very large bandwidth enables highly accurate localisation but the typically smaller ranging coverage makes it more suited for short-range applications. Other state-of-the-art systems rely on user interaction or route prior knowledge but this is not always wanted or even possible [2]. In this paper, an advanced indoor localisation algorithm for tracking a person in real-time through a building, is presented. To avoid expensive hardware costs or a time-consuming measurement campaign, the existing WiFi or ZigBee infrastructure and an advanced network planner are used.

II. Methodology

A. Localisation algorithm

The localisation algorithm is based on the Viterbi algorithm [3]. This dynamic programming algorithm is used to determine the most likely sequence of hidden states, called the Viterbi path, resulting in the sequence of observed events. To apply this technique on a localisation algorithm, the states have to be interpreted as real locations on a floor plan. Then, this principle comes down to determining the most likely sequence of positions instead of only the most likely current position. All possible trajectories are kept in memory and each trajectory has an associated cost. This cost is the sum of Mean Square Errors (MSE) between measurements and reference values (see Section II-C) and is used as decision metric. To apply the Viterbi principle in a useful manner (improve the accuracy), we have to restrict the number of allowed transitions between two consecutive locations. Therefore, we use semantic data: the environment of the object that is being tracked and an adjustable maximum speed. In this way it is assured that no walls are crossed (doors are used to leave a room) and no unrealistically large distances are crossed within a given time frame. Overall, this leads to realistic and physically possible trajectories. To the best of the author's knowledge this is the first localisation algorithm that uses this combination of techniques.

B. Start position

Because the most likely sequence of positions is determined, the developed localisation algorithm is sensitive to a wrong start position. One could start off in the wrong room, which implies a certain recovery time before predictions can be accurate again, because walls cannot be crossed. To counteract this, additional start positions are added as soon as the tracking begins. These additional start positions lie on circles around the best initial prediction. In this way the algorithm can easily correct itself by switching to another trajectory when new measurements suggest being located inside a different room. By using this technique also the previous positions will be set right.

C. RSSI fingerprinting using heuristic indoor network planner

The developed localisation algorithm relies on a Received Signal Strength Indicator (RSSI) fingerprinting technique to estimate the most likely position by comparing the measurements with reference values from a radio map. This radio map (also known as fingerprint database) contains the path losses to all fixed nodes, for each possible position (grid point) on the floor plan where the localisation takes place. The size of the fingerprint database will depend on the size of the floor plan, the resolution of the possible positions (grid size) and the number of access points (APs). The path losses can be calculated with a theoretical model or obtained via a measurement campaign. Because the latter is an expensive and time consuming process, a network planner was used (WHIPP [4]). This approach results in a slightly reduced accuracy but allows an immediate deployment. The network planner uses an advanced heuristic model to predict the path loss between an AP and a certain location. Three contributions are taken into account to calculate the total path loss: the sum of the distance loss along the path, the total wall loss along the path, and the interaction loss along the path.

To estimate the improvement of the developed localisation algorithm, a basic algorithm is used for comparison. This basic localisation algorithm relies only on the RSSI fingerprinting technique without the added intelligence (i.e. Viterbi principle and semantic data).

D. Configuration

The experiments are conducted on the third floor of an office building in Ghent (*w-iLab.t office testbed* [5]), which measures 90 m by 17 m and consists of several computer classes, offices and meeting rooms. In Figure 1, a part of the floor plan is shown: the core consists of concrete walls (gray walls), the inner structure is movable and made of layered drywall (brown walls) and the doors are made of wood (yellow walls). The wireless network consists of 57 fixed nodes that were installed on a height of 2.5 m (blue dots in Figure 1). When using a grid size of 1 m this results in 1573 grid points or 89661 reference path loss values ($1573 \cdot 57 = 89661$), which results in a fingerprint database of 350 KB (if we reserve 32 bit for each value). Nine realistic test trajectories with an average length of 87 m were outlined on the floor plan. Figure 1 shows one such test trajectory (red) and its reconstruction (black), the starting point is marked with a black dot.

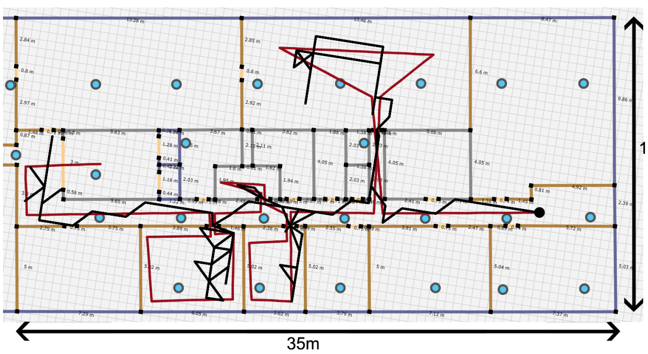

Figure 1. Part of the floor plan with a test trajectory and its reconstruction

III. Evaluation

A. Simulation

For the simulations, the reference values from the fingerprint database are used as input for the localisation algorithm (i.e., path loss values from the positions along one of the nine test trajectories). To simulate real measurements a certain amount of Gaussian noise is added to these reference values. Next, the accuracy of the reconstructed trajectories is calculated for an increasing level of added noise: 0 - 20 dB (i.e., the standard deviation of the added Gaussian noise with zero mean). Two localisation systems are used to reconstruct the trajectories: the developed localisation algorithm and the basic fingerprinting technique. These experiments are repeated ten times for averaging. In Fig. 2, the mean and standard deviation of this accuracy are plotted as a function of the added level of noise.

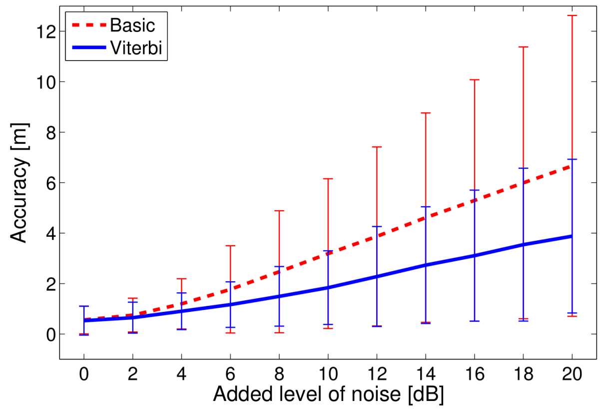

Figure 2. Accuracy as a function of the added noise (simulation)

Fig. 2 shows that the developed Viterbi algorithm always outperforms the basic one, in terms of both mean accuracy and standard deviation. Compared to the basic algorithm the results were on average 2.78 m more accurate (3.88 m versus 6.66 m) with 2.92 m less standard deviation (3.04 m versus 5.96 m), for the worst test case. The improvement in accuracy can be explained by the added intelligence in general. The smaller standard deviation can be explained by the combination of taking the previous positions into account and a maximum speed which makes the localisation algorithm more robust to measurement deviations and outliers.

B. Experimental validation

This time, the test trajectories are conducted by a human who hand-carried a mobile node with an antenna gain of 5 dBi. Two wireless technologies were tested: ZigBee and WiFi. The same two localisation algorithms were used to reconstruct the same nine trajectories. The results can be found in Table I.

Table I
MEAN ACCURACY (M) AND STANDARD DEVIATION (S)

Algorithm →	Basic		Viterbi		Improvement	
Mobile node ↓	M [m]	S [m]	M [m]	S [m]	M [%]	S [%]
ZigBee	2.96	3.63	2.18	1.31	26.4	63.9
WiFi	3.38	3.13	2.2	1.46	34.9	49.4

Again the developed localisation algorithm was more robust and achieved a better mean accuracy with lower standard deviations than the basic algorithm. The relative improvement in mean accuracy and standard deviation is 26.4% and 63.9% for the ZigBee node and 34.9% and 49.4% for the Wifi node, respectively.

C. Sensitivity Analysis

In this section a sensitivity analysis is conducted, based on the measurements from the experimental validation with the mobile ZigBee node. This is important to estimate the influence of the localisation algorithm parameters on the performance.

The majority of testbeds used for testing a new localization system have a very high node density. In a typical environment this node density is typically much lower. When using only 10 out of the 57 fixed nodes, we obtain a mean accuracy of 6.58 m with the basic algorithm and 3.26 m with the developed algorithm. As expected the accuracy is a bit lower but the relative improvement compared to the basic algorithm is bigger: 50.5% when 10 fixed nodes are used versus 26.4% when all nodes are used.

The average time needed to calculate one location update will determine the ability for real-time usage and will depend on the available computational power but also on the used grid size and number of paths retained in memory. When using a grid size of 1 m and retaining only the 100 best paths with every location update, we obtain a calculation time of 1.5 ms whilst having no loss in accuracy (compared to the situation when all paths were retained in memory). This experiment was conducted on a desktop computer with an Intel Core i7 3.40 GHz processor and 8.00 GB DDR3-SDRAM.

IV. Conclusions

In this work, a real-time localisation system based on the Viterbi algorithm and semantic data was developed. The advantage of this system is the independence of the used wireless technology or specific indoor environment. The intelligence is added to the localisation algorithm itself, so there is no need for extra hardware costs. A network planner was used to construct the fingerprint database, so there was also no need for an extensive measurement campaign. Compared to a basic algorithm, the predictions were more accurate and there was a huge improvement in standard deviation. More concrete: the mean accuracy and standard deviation improved by 26.4% and 63.9%, respectively. In a sensitivity analysis it was shown that the advantage of the developed localisation algorithm compared to the basic algorithm was even bigger in lower node densities and that it is able to work in real-time. In general, it can be embedded in both existing and future localisation algorithms to further improve the accuracy.

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